The Faults in our Star Clusters: Predicting Globular Cluster Evolution using Neural Networks

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I. Context

Globular cluster mass loss provides insight into high-redshift star and galaxy formation

Globular clusters (GCs) are large, spherical, dense **stellar systems** that formed with their host galaxy >10Gyr ago. Their mass and structure are altered by the host galaxy as they evolve. **Studying GCs** gives us clues about the **formation and evolution of stars and galaxies** which is difficult to observe directly.

III. Methods

We train a neural network to intake a tidal tensor, along with other parameters, and predict the expected mass loss



Neural networks use

hidden layers and neurons to **emulate how humans learn** – reinforcement learning

II. Motivations

GC mass loss is computationally expensive and time-consuming to model with traditional simulations, limiting depth of study



The **gravitational field** tidally strips stars from a GC, with tidal heating from substructure accelerating the process. However, this is **difficult to study** with direct N-body or large-scale cosmological simulations. Deep neural networks **(DNNs) can approximate any function** and have constant computational burden after training [1], making them **ideal for predicting GC evolution**.

A tidal tensor is a way of characterizing the strength of the tidal field at a given location in the galaxy [2]. We train a DNN to intake the maximum eigenvalue of the tidal tensor (λ_{max}) , duration of shock (dt), current mass (m_c) , and rate of change of the tidal tensor $(\frac{d\lambda_{max}}{dt})$ to predict the expected mass loss (dm). Full evolutionary tracks and dissolution times can be obtained from the full tidal histories of a given cluster.

through trial and error.

Modelling Stages

Step 1: Univariate model, simplified histories

Step 2: Multivariate model, simplified histories

Step 3: N-body data: >200 clusters

Neural nets can predict globular cluster evolution



~400 times faster than

traditional methods

IV. Results

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Actual vs. Predicted Dissolution Times



100 histories were predicted in ~15 hours, compared to 400 CPU days
 Mean residual is small on individual predictions (-0.1)
 Outliers that were not considered in training were present in the full histories,

Full Evolutionary Tracks – Select Clusters



NN model is versatile: current formalism is only applicable to circular and

eccentric orbits [3]
 Also has the benefit of predicting mass values,

rather than just dissolution

times

Limited in that inner

Actual Dissolution Time [Gyr]

contributing to the deviance from the true value workings of network is a black box – impact of variables is unknown unlike a regression model

V. Future Work

The next steps would be to further improve the network's accuracy and optimize the code. This would mean training on a larger data set, expanding the parameter space to find the optimal combination of inputs, including using all the tidal tensor eigenvalues or components, and exploring other cluster properties that can be predicted.

VI. References

[1] Breen, P.G., Foley, C.N., Boekholt, T., Portegies Zwart, S., 2020, MNRAS 494(2),2465–2470

[2] Webb J. J., Reina-Campos M., Kruijssen J. M. D., 2019, MNRAS, 486, 5879[3] Baumgardt H., Makino J., 2003, MNRAS, 340, 227